EFFECTS OF EXPLANATION TO SELF AND OTHERS WITH MENTAL MODEL DIAGRAMS DURING SCIENCE LEARNING

by

Kelly Renée Summers

A thesis submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Educational Psychology

The University of Utah

August 2015

T h e U n i v e r s i t y o f U t a h G r a d u a t e S c h o o l

STATEMENT OF THESIS APPROVAL

The thesis of Kelly Renée Summers

has been approved by the following supervisory committee members:

Kirsten Butcher	, Chair	**04/14/2015** Date Approved
Anne Cook	, Member	**04/14/2015** Date Approved
Robert Zheng	, Member	**04/14/2015** Date Approved

and by **Anne Cook**, Chair/Dean of

the Department/College/School of **Educational Psychology**

and by David B. Kieda, Dean of The Graduate School.

ABSTRACT

This study examined the use of diagram representations (correct or correct and incorrect models) when combined with self-explanation or explaining to another in a learning environment. Thirty-five learners with low prior knowledge were assigned to one of four conditions: self-explain with a correct model, self-explain with both correct and incorrect models, explain to another with a correct model, or explain to another with both correct and incorrect models. Results at posttest showed that explaining to another increased declarative knowledge development. Scores on inferential knowledge suggest an interaction, such that learners may learn more with comparison models when self-explaining to themselves, but learn more from correct models when explaining to another. These finding suggest that learners may benefit from different materials when learning activities include content production for others as compared to study by oneself.

To my Father, who inspires me.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table

CHAPTER 1

INTRODUCTION

A review of the educational technologies of the twentieth century shows that, other considerations aside, simply adopting a technology-centered approach to providing learning materials fails to produce lasting improvements in education. The use of technology itself does not guarantee that learning will occur. When technology is used just as the delivery system for the instruction, no significant improvement in learning is achieved beyond traditional materials (Clark, 1983). Education has witnessed a common cycle of technology adoption, from television, to computers, to the internet, and more recently, to devices like the iPad and tablets. It begins with a promise of how the new technology will revolutionize education, continues with a rush to implement the new technology into schools, and ends with unmet hopes and expectations (Tenorio, 2003). Kozma (1991) has suggested that it is not the media delivery system that influences learning, because some students will learn regardless of the delivery system. However, he contends that media can play an important role in education when it is used by learners to build on prior knowledge and to construct new knowledge (Kozma, 1991). Thus, Kozma has argued that it is time to stop asking *if* media influences learning in order to determine *how* the capabilities of media can be used to support learning for particular learning contexts (Kozma, 1994). Taking a student-centered approach to the design and implementation of technology for learning first requires attention to the nature of student learning in digital environments.

CHAPTER 2

SELF-REGULATED LEARNING

Modern students learn frequently with digital content and multimedia, with some research finding that students report online searches to be their primary source of academic material (Graham & Metaxas, 2003). Learning in online contexts is often characterized as a self-regulated learning task (Moos & Azevedo, 2008). Self-regulation refers to an individual's ability to manage their own learning activities in order to achieve a learning goal. Self-regulated learning processes include planning, monitoring, and strategy use (Azevedo, Moos, Greene, Winters, & Cromley, 2008). Additional self-regulated processes used by active learners are: attention, persistence, time management, and effort (Sitzmann & Ely, 2011). Each of these processes involves cognition at the level of knowledge processing (Winne, 1995). Self-regulation processes themselves do not create knowledge, but are considered to be necessary for learning in many contexts (Eysink & de Jong, 2012). During self-regulated learning, learners make decisions about what they want to learn, how they will learn, how much time they set aside for learning, etc. Students may set goals and utilize and adjust strategies to achieve those learning goals (Azevedo, Cromley, & Seibert, 2004). Students who successfully self-regulate are able to recognize and control their learning goals (Ariel, 2013).

Despite the importance of self-regulated behaviors for learning, many learners struggle to regulate their own learning (Al-Harthi, 2010). Students often do not engage in planning activities, like setting learning goals and activating prior knowledge (Azevedo, Guthrie, & Seibert, 2004).

Although few students spontaneously self-regulate their learning effectively, those learners who do engage in effective self-regulated learning processes learn more deeply with online materials (Azevedo, Guthrie, et al., 2004). Azevedo, Guthrie, and Seibert (2004) examined the role of self-regulated learning in facilitating students' shifts to a more sophisticated understanding of the circulatory system. They found that high achieving participants used effective self-regulating strategies in their learning. These high achieving participants set learning goals and subgoals, activated prior knowledge, monitored their new understanding, and planned their time and effort. In contrast, low achieving participants demonstrated an inability to engage in necessary self-regulating processes (Azevedo, Guthrie, et al., 2004). Thus, students may need external support in order to engage in these self-regulated learning behaviors that facilitate deeper understanding during online learning.

Previous research has found that providing support or training can help students engage in self-regulated learning processes, resulting in improved learning outcomes. Azevedo et al. (2008) studied self-regulation with hypermedia when students were provided with external support for self-regulation or spontaneously self-regulated while learning about a difficult science topic: the circulatory system. External support for self-regulation was provided in the form of a human tutor who prompted self-regulated processes during an online learning task. In the control condition, students learned without any external prompting. Compared to students who self-regulated their own learning, participants who received self-regulation support from the tutor demonstrated a more complete understanding of concepts at the end of the study (Azevedo et al., 2008). Participants who relied on their own spontaneous self-regulation demonstrated gains in declarative knowledge but not on mental model development, suggesting that self-regulation is particularly important to the development of deeper understanding as assessed by mental models. These results were consistent with previous findings (Azevedo, Guthrie, et al., 2004). Thus, it is important to consider the nature of mental models and the degree to which they should be considered as evidence for deeper learning during self-regulated learning tasks.

CHAPTER 3

MENTAL MODELS

A mental model can be described as a concept held internally that represents how a person understands a concept (Rook, 2013). In research on multimedia and online learning, mental models are used as a holistic assessment of the overall understanding a person has about a specific topic or process (Butcher, 2006; Gadgil, Nokes-Malach, & Chi, 2012). Chi et al. (1994) described mental models as a collection of beliefs, comprising an internal representation of an interrelated system of concepts that can be simulated mentally. The mental model, then, can be defined as an integrated, coherent understanding of a system or concept that drives inference about system behaviors and functionality.

Some research has used “think-aloud” protocols to assess students’ overall mental model understanding, using verbalizations during learning and responses to a series of prompts to derive components of the mental model (Chi, De Leeuw, Chiu, & Lavancher, 1994). Other research has assessed mental models by asking learners to draw and explain diagrams or visual images that demonstrate an overall function or system (Butcher, 2006; Gadgil et al., 2012). The use of diagrams may be particularly helpful for learning about concepts that have a significant visual component (e.g., science, engineering), as diagrams can be used to convey spatial knowledge (Bryant & Tversky, 1999). Butcher (2006) asked participants to draw a diagram that showed their understanding of how the heart and circulatory system worked, starting with a blank sheet of paper. Gadgil et al. (2012) also asked participants to draw diagrams that explained the workings of the heart and circulatory system, using a basic outline of the body that participants completed. In both cases (Butcher, 2006; Gadgil et al., 2012), the types of mental model diagrams generated by participants were a close match to those derived from extensive verbal data (Chi et al., 1994).

In many cases, a person's existing mental model may be false or incomplete and, therefore, will conflict with new knowledge gained in a learning setting and require revision (Vosniadou, 2008). Mental model revisions may be achieved by addressing relationships between new knowledge and existing or prior knowledge. This process of reconciling new and prior knowledge requires knowledge refinement and reorganization, rather than replacement as a primary metaphor for learning (Smith, diSessa, & Roschelle, 1993).

Mental models can be revised by using known strategies (Butcher, 2006; Crowley & Siegler, 1999; Rittle-Johnson & Star, 2007; Wilke & Losh, 2012) that include reading refutation texts that identify common misconceptions (Braasch, Goldman, & Wiley, 2013), identifying interrelationships between features of the existing mental model and the new knowledge (Gadgil et al., 2012), explaining texts (Chi et al., 1994), viewing of multimedia materials (Butcher, 2006) that depict the new knowledge, and comparing one's existing mental model with the correct model (Gadgil et al., 2012).

Existing research has demonstrated that not all of the aforementioned strategies for revising mental models are equally effective. Gadgil et al. (2012) examined the different kinds of cognitive processes involved in revising an incorrect mental model. Gadgil et al. (2012) found that the knowledge revisions necessary for changing a mental model were more likely to occur when an incorrect model was compared and contrasted with an expert model. Gadgil et al. (2012) argued that the process of comparison facilitated the awareness of particular (key) features over others as well as promoting analysis of how those key features differed across representations. If revising a mental model requires the learner to identify and address important discrepancies between his or her prior knowledge and incoming information, a key question is what learning strategies may facilitate this process of identifying and reflecting upon mental models. One well-studied instructional approach that is used to help learners articulate and reflect upon instructional materials is self-explanation.

CHAPTER 4

SELF-EXPLANATION

Self-explaining is the process of generating explanations for oneself during learning, which can serve to identify incorrect prior knowledge and to help the learner build on or make connections to prior knowledge as new knowledge is learned (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). Chi et al. (1989) identified self-explanation as an effective learning strategy via the analysis of spontaneous verbal self-explanations generated by students who were solving physics problems. In this study, students who learned more from problem solving were found to devote significant effort to explaining the content of problems to themselves as they worked; in contrast, students who learned little from problem solving did not engage in these explanations. Chi et al. (1989) concluded that self-explaining is a mechanism of study that allows students to infer and explicate based upon gaps in their knowledge and understanding. The potential of self-explanation to highlight knowledge gaps is supported by research showing that students who spontaneously explained examples to themselves made more accurate self-assessments of their understanding (VanLehn, Jones, & Chi, 1992).

Because self-explanation originally was identified during spontaneous study, additional work was conducted to determine if most students could benefit from self-explanation as a learning strategy (Chi et al., 1994). This research compared students who were trained to self-explain as they learned from correct worked examples in mathematics to students who were not trained to self-explain (and therefore engaged in spontaneous processes) as they studied the same materials. Results showed that the trained self-explainers learned significantly more during study than students who explained spontaneously. Further, the amount of improvement was proportional to the amount of self-explanation generated. Williams and Lombrozo (2010) argued that the process of explaining leads learners to interpret what they are studying in terms of unifying patterns, which promotes discovery and generalization of knowledge, and supports overall learning.

Although early research on self-explanation focused on learning with traditional, text materials (Chi et al., 1989; Chi et al., 1994), there is research evidence that self-explanation is effective with visual content (Ainsworth & Loizou, 2003) and multimedia materials (Butcher, 2006). Research has also found that self-explaining multimedia materials led to greater engagement in the learning process in general, and more elaborative processes in particular (Eysink & de Jong, 2012). Eysink and de Jong (2012) compared four learning conditions with multimedia materials: hypermedia learning, observational learning, self-explanation learning, and inquiry learning. The self-explanation and the inquiry learning conditions had the highest learning outcomes and these participants were more engaged in the learning processes. These results suggest that elaborative explanation (as in the self-explanation condition) is a key process that can help to explain differences in learning across different instructional approaches within multimedia learning environments.

In another study, researchers examined the self-explanation effect with learners studying the human circulatory system (Ainsworth & Loizou, 2003). In this study, participants used either text or diagrams. During study, students generated self-explanations about the topic. Students who self-explained the diagrams performed significantly better on posttests than students who self-explained the text materials. Students in the diagram condition produced significantly more self-explanations than students in the text-only condition; furthermore, students who spontaneously generated a large number of self-explanations scored over twice as high on a posttest as those who gave fewer explanations (Ainsworth & Loizou, 2003). Butcher (2006) found similar results to Ainsworth and Loizou (2003) in that learners who saw diagrams learned science concepts more deeply as they self-explained. Butcher’s analyses of self-explanation utterances showed that students were more likely to engage in high-level processing during self-explanation with diagrams versus text alone.

CHAPTER 5

EXPLAINING TO ANOTHER

Because generating explanations during self-explanation is thought to facilitate learning via the activation of prior knowledge and the generation of inferences, other forms of explanation may also be predicted to support learning when students generate them during study. For example, explaining to another could be hypothesized to be even more effective than self-explanation. Despite the documented benefits of self-explanation, when a person self-explains, his or her verbalizations may include fragmented, incomplete, and even incorrect utterances (Chi et al., 1989). Eysink et al. (2009) suggested that self-explaining lends naturally to explaining study materials to a partner. He suggested that as long as the partners have similar levels of prior knowledge and the explanations are understandable to both partners, collaboration in an explanation-based learning environment is likely to lead to similar or even better results than with just self-explaining alone (Eysink et al., 2009).

Despite the potential value of explaining materials to a peer, research has found that not all peer-produced explanations are equally helpful in supporting learning (e.g., Coleman, 1998; Roscoe & Chi, 2008). Coleman (1998) found that peer tutors who generated explanations that incorporated knowledge-building elaborations seemed to learn more effectively (as they engaged in tutoring activities) than tutors who only summarized general knowledge. However, knowledge-building may not be a natural approach to tutoring for untrained individuals. Chi (2007) found that many tutors adopted a knowledge-telling form of explanation; that is, they tended to summarize the provided content for tutees and failed to reflect, monitor, and integrate new knowledge into their own prior knowledge.

Roscoe and Chi (2008) compared two kinds of explaining to another person. In one condition, peer tutors were told to explain and go beyond the information provided in a set of text materials with the stated purpose of helping the tutee really understand the learning materials. The tutee was allowed to interact with the tutor (e.g., ask questions). In another condition, tutors were encouraged to go beyond the text to create a lesson that could be used by another student. These tutors produced a videotaped explanatory lesson. When students in the video explanation condition were compared to the students in peer tutoring condition, the students who engaged in peer tutoring scored higher on the posttests (Roscoe & Chi, 2008). Thus, the presence of a peer during an explanation opportunity may serve to prompt the explainer to move from summarizing knowledge to (deeper) knowledge-building processes, perhaps through questions or other comments. Roscoe and Chi (2008) also included a self-explanation condition in their study, allowing a direct comparison between self-explanation and video explanations in supporting learning. Their results showed that self-explanation was significantly better than creating a video explanation, likely because students who self-explained engaged more frequently in knowledge building than students who created a video explanation. Students who created video explanations were more likely to rely on summarization and failed to engage in significant analysis or comparison as they explained. Roscoe and Chi (2008) concluded that self-explanation should be a more effective process than explaining to a nonpresent peer because it targets customized repair and analysis of a learner’s existing mental models.

Similar to Roscoe and Chi (2008), Hoogerheide et al. (2014) conducted a study that included a condition in which learners recorded an explanatory lesson for others using video. Hoogerheide et al. (2014) studied the effects of asking learners to study a text with the intent to create an instructive video (explain to another) versus with the intent to take a test. Their hypothesis was that the learner might invoke a more active study approach when the goal of study was to create a video explanation for others, thus resulting in improved learning outcomes. In order to tease apart the impact of intention *during study* with the effects of actually recording an explanation after study, Hoogerheide et al. (2014) used three conditions. Half of the students in the explain to another condition were required to actually explain the text to another by creating an instructional video; the other half did not actually create the video as they had been led to expect. Therefore, Hoogerheide et al. (2014) actually compared three conditions: study intention + no video; explain intention + no video; explain intention + video explanation. Students who recorded a video explanation showed significantly better overall learning in the posttests as compared to both the study intention and the explain intention + no video conditions (Hoogerheide, Loyens, & van

Gog, 2014). It is interesting to note that, according to the transfer portion of the posttest, stronger transfer performance was observed in the explain intention + no video group on the immediate posttest, but transfer on the delayed posttest was strongest in the explain intention + video explanation group. Together, these results suggest that producing an explanation that is intended for others can improve deep learning outcomes and that this effect cannot be explained by differential processing during study.

One difference between the Roscoe and Chi (2008) and Hoogerheide et al. (2014) study was in the materials that the students used as they produced their explanations. In Roscoe and Chi (2008), students produced explanations from text-only materials and did not have access to visuals during the explanation process. In contrast, students in the Hoogerheide et al. (2014) study used a visual aid (in the form of a summary table showing the four forms of syllogistic reasoning) during explanation. Just as self-explaining diagrams and multimedia materials lead to greater learning than self-explaining text-only materials (Ainsworth & Loizou, 2003; Butcher, 2006), it is possible that explaining to another while using visual materials will improve the quality and effectiveness of those explanations. Further, just as learners engage in deeper processing when self-explaining with multimedia materials (Butcher, 2006), individuals explaining to a (nonpresent) peer may engage in deeper processing when creating explanations that are supported by multimedia content. This possibility will be tested in the current study. However, the extent to which explanations may exhibit knowledge building versus knowledge telling may depend upon the extent to which multimedia materials facilitate summarization versus comparison. As discussed below, multimedia materials that promote comparison processes may be more effective at building deeper understanding during study.

CHAPTER 6

COMPARISON

When multiple materials or representations are available or generated during a learning opportunity, learners may benefit from explicit comparison across these materials. Siegler (2002) studied young children explaining their answers on math problems to adults. The first group explained their own answers to another, then they were given feedback on whether the answer was correct or not. The second group explained a correct answer to the problem. The third group explained why the correct answer was correct and also explained why an incorrect answer was wrong. The results of this study showed that children as young as 5 benefited from explaining to another both correct *and* incorrect answers (Siegler, 2002). Explaining to another the correct answers *and* incorrect answers may allow a person to make comparisons between the two examples that spur explicit analysis of the relationships between the correct and incorrect examples, thus providing opportunities for mental model revision. Rittle-Johnson and Star (2007) studied comparing solution methods as a fundamental learning mechanism. One condition compared multiple worked-out solutions including shortcuts and another condition learned from studying sequentially presented solutions. Rittle-Johnson and Star (2007) found that students in the compare condition made greater gains in procedural knowledge, and were better able to transfer their knowledge to new problems. However, students overall did not differ in their conceptual knowledge gains. Thus, comparison processes may serve to increase the robustness of knowledge without changing the nature of the knowledge that is developed during learning.

Gadgil et al. (2012) studied learning with diagrams that represented flawed mental models and expert models under two conditions. In one condition, the learner was prompted to self-explain the expert model alone. In another condition the learner self-explained or compared their (initially) flawed mental model (as depicted in a self-generated diagram) to an expert model. Learners who made comparisons were more likely to acquire a correct mental model and to exhibit deeper understanding of the systems in the model than those who were prompted to self-explain the expert model alone. Gadgil et al. (2012) argued that the process of comparing the differences in an expert-generated versus a self-generated model led the learner to detect misunderstandings or gaps in their current knowledge, leading to knowledge transformation. However, it also is possible that the presence of multiple representations of varying accuracy simply allowed the students to move from a knowledge-telling approach to a knowledge-building approach. That is, it is not clear if the personalized repair of mental models leads to effective learning via comparison or if the process of comparing multiple (correct and incorrect) representations is advantageous in the quality of explanation that it supports. Therefore, it is an open question whether or not comparison processes will improve learning when students generate explanations for a nonpresent peer.

CHAPTER 7

CURRENT RESEARCH

The current research examined the impact of explanation type (self-explaining vs. explaining to another) with different external representations or material types (a correct mental model vs. correct and incorrect mental model).

Research Questions

1) Is self-explanation more effective than explaining to a nonpresent peer when visual mental models are used during explanation?

2) Is explaining with the correct and incorrect mental models more effective than explaining with the correct mental model alone when recording a video explanation for a nonpresent peer?

CHAPTER 8

METHOD

Participants

Participants were 58 undergraduate students (18 males, 39 females) at the University of Utah enrolled in courses in the College of Education. Three participants were excluded from data analysis due to computer error (resulting in data loss) or participant failure to follow instructions, leaving 55 participants with data to examine. Of the 55 participants, at the conclusion of the study, 20 participants were considered high prior knowledge learners (after examining their pretest scores) and were excluded using the Gadgil et al. (2012) exclusion criteria. The remaining 35 participants had been assigned randomly to one of the four experimental conditions (see Table 1). Participants received partial class credit for participation.

Design

The study utilized a 2 (explanation type) X 2 (representation type) factorial (see Table 1).

Materials

Demographic information. At the beginning of the study, all participants completed a demographic questionnaire, which asked participants to report their

Table 1

Description of experimental conditions and final sample size.

	Self-Explain	**Explain to Another**
Correct Model	Students self-explained the correct mental model of the heart and circulatory system. *n* = 9	Students recorded a video explanation of the correct mental model of the heart and circulatory system. *n* = 6
Correct & Incorrect Models	Students self-explained the correct and incorrect mental model of the heart and circulatory system. *n* = 11	Students recorded a video explanation of the correct and incorrect mental model of the heart and circulatory system. *n* = 9

age, whether English was their native language, and any previous science courses taken in high school and college. They also were asked if they had in the past participated in any previous research studies that involved learning about the heart and circulatory system.

Pretest & posttest. Before and after studying the materials and creating their explanations, all students completed a pre- and posttest to assess their knowledge about the human heart and circulatory system. The pre- and post-tests contained mental model and declarative knowledge questions. Only the posttest included inference questions. All pre- and posttest questions (mental model, declarative knowledge, and inference) were the same questions as used in previous research by Gadgil et al. (2012).

Mental model. Six short answer questions were included in the pre- and posttest to assess students' knowledge about the overall function of the human circulatory system. These questions targeted system-level information about the functions and pathways critical to the heart and circulatory system. For example, "Describe in a few lines the path of the blood in the circulatory system. What is the main function of the heart?" The scoring for this section was determined by points assigned for each key term present and the correct distinction between structure, pathway, and function. Up to 20 points were possible. Scoring used the rubrics established by the Gadgil et al. (2012) study.

Declarative knowledge*.* Twelve declarative knowledge questions were included in the pre- and posttest. These questions asked students to define key vocabulary terms relevant to the human heart and circulatory system. All key terms were preceded by the same prompt: "Please define the following term. Include information about its location and function." Example terms included: Aorta, Valve. Up to 22 points were possible overall; 10 questions had a maximum possible value of two points and two questions had a maximum value of one point each. As in Gadgil et al. (2012), one point was awarded for correctly describing the term and one point for the description of its function.

Inference*.* Eighteen inference questions were used on the posttest. Inference questions were not addressed in the prior tests. These questions were designed to assess the participants' ability to make inferences about functions within the circulatory system. To answer these questions correctly, participants must make connections between the text and their prior knowledge. For example, "Explain how blood travels from the left ventricle to the various parts of the body” and “Why is the heart divided into chambers?” Scoring followed rubrics established by Gadgil et al. (2012), with 25 points possible on the overall assessment and questions assigned either one or two points in value.

Mental models selection task. The models selection task was designed using four of the simplified heart model diagrams from previous research (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001). In addition to the visual mental models, the task presented students with a series of simple questions addressing required conceptual knowledge related to specific mental models of the heart and circulatory system (e.g., “Blood circulates” and “Vessels (Arteries/veins) transport”) as outlined in previous research (Azevedo & Cromley, 2004; Chi et al., 2001).

Mental models presented during this task ranged from least complex (and, correspondingly, least correct) to most complex (and fully accurate) diagrams. The participants were asked a series of true/false questions related to the mental model; the diagram of each mental model was shown at the end of the series of questions (see Figure 1). When the mental model diagram was presented, participants were asked, “Does this diagram show the correct path of the blood?” If the participant selected “yes” for this question, the mental models task ended and the selected (incorrect) diagram of the mental model was then used as the comparison mental model if the participant was placed in the “correct/ incorrect models” condition.

If the participant selected “no”, another series of true/false questions were asked related to the next more complex mental model; following these questions,

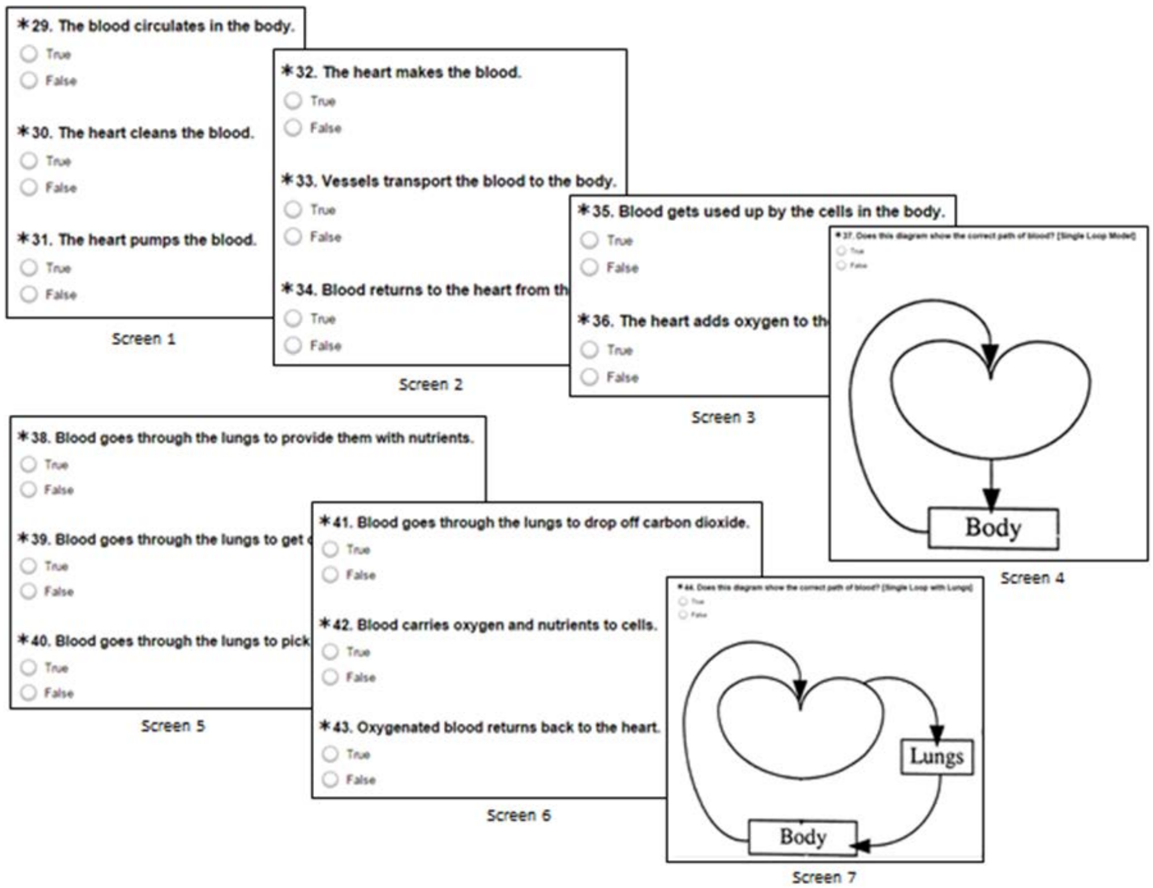

Figure 1. Sample screen content and order from the mental model selection task.

the mental model diagram was shown and participants again were asked, “Does this diagram show the correct path of the blood?” Again, if the participant selected “yes” for this question, the mental model task ended and the selected (incorrect) diagram of the mental model was then used as the comparison mental model if the participant was placed in the “correct/ incorrect models” condition. This procedure repeated until the participant selected a mental model or the most complex mental model diagram was presented.

The heart selection task was administered via the computer (using SurveyMonkey). At each level, two or three questions were shown per slide for a total of six to eight questions about the necessary features for each mental model level (see Appendix A).

Text. Each participant was given the same text about the human circulatory system (Shier, Butler, & Lewis, 2006). The text was studied by all participants. The human circulatory system text contained 72 lines describing the human heart and circulatory system from Gadgil et al. (2012).

Procedures

All experimental sessions took place in a computer lab. Each participant was seated at a personal computer equipped with a screen recording software (e.g., Snag-It) and a headset with a microphone.

Upon arrival at the study, students received information about the informed consent procedure. At this time, they were asked if they had any questions about the study and their participation. Next, the students were assigned a random number and letter. The number served as a unique identifier for their experimental data. The letter served as the condition in which they were assigned.

The participants took the demographic questionnaire online using their assigned number to connect this information with their pre- and posttest study results. The demographic section of the study took about 5 minutes to complete.

The participants took the pretests online (mental models and declarative knowledge). This portion of the study took about 25 minutes and was self-paced. Participants were instructed to give their best guess if they were unsure of the answer to a question.

Next, participants completed the mental models selection task online. The mental model selection task was also self-paced, and took no longer than 5 minutes.

Following the mental models selection task, all participants were given a pdf version of the human circulatory system text and were instructed to study the text for 20 minutes.

At the completion of 20 minutes, participants who were assigned to the "self-explain" conditions spent 5 minutes self-explaining the materials as they viewed the diagram(s) appropriate to their representation condition (either the correct mental model only or both the correct and incorrect mental models). Participants' screen and voices were captured during the self-explanation phase. A set of self-explanation prompts were provided to students on paper (e.g., "How do the materials change your initial understanding or ideas about how the system works? What questions do you have about how the heart and circulatory system work?"), but the experimenter did not verbally prompt the students. Participants were instructed that this was their final opportunity to learn as much as they could before testing and that they should be sure that their self-explanation provided a thorough explanation of what they learned and how the human circulatory system works.

Participants who were assigned to the "explain to another" conditions had 5 minutes to create an explanation about how the heart and circulatory system works that could be used by another person. Participants' screens and voices were recorded as they explained. A set of "good explanation" prompts modeled on self-explanation prompts were provided to the participants; participants were told to use these prompts to help them develop their explanation. For example, instead of asking, “What questions do you have about the heart and circulatory system?” the prompts ask, “What questions **would a person have** about how the heart and circulatory system work?”

After the completion of the tasks listed above, all participants completed the three-part, online posttest. Participants were instructed to give their best guess if they were unsure of the answer to a question. The posttest portion of the study took about 25 minutes.

The last 5 minutes of the study were reserved for debriefing and participant questions.

CHAPTER 9

DATA ANALYSES

For data analysis, the exclusion criteria of Gadgil et al. (Gadgil et al., 2012) were used to select only participants with low prior knowledge. Participants who arrived with a single loop mental model and scored 10 points or less on the mental model as well as on the declarative knowledge pretest were included in the analysis. This resulted in 35 participants divided among the four experimental conditions (see Table 2). Participants' scores on pretest measures were correlated with scores on posttest measures (see Table 3). Overall, assessment scores tended to be significantly and positively correlated.

A multivariate analysis of variance was conducted to check for condition differences at pretest. No significant multivariate effects were found for explanation target ($F_{(2,30)} = 2.7$, $p = .09$, $\eta_p^2 = .15$), representation type ($F < 1$), or the two-way interaction ($F_{(2, 30)} = 1.3$, $p = .29$, $\eta_p^2 = .08$). The trend for an explanation target main effect was driven by results for mental model scores ($F_{(1, 30)} = 2.6$, $p = .03$, $\eta_p^2 = .14$) with no effect on declarative knowledge ($F < 1$). Mental model pretest scores were significantly, positively related to all posttest measures; thus, - mental model pretest scores were used as a covariate in posttest analyses.

Table 2

Experiment 1 means and (standard deviations) for pretest and posttest assessment items.

		Representation Type			
		Correct Model		Correct and Incorrect Model	
		Self-Explain	Explain to Another	Self-Explain	Explain to Another
		n = 9	*n* = 6	*n* = 11	*n* = 9
Pretest					
	Mental Model Score	6.1 (2.4)	2.8 (2.5)	4.6 (2.0)	4.0 (2.9)
	Declarative Knowledge Score	2.1 (1.5)	1.7 (0.8)	2.1 (1.9)	2.3 (1.6)
Posttest					
	Mental Model Score	11.1 (3.2)	8.7 (3.8)	9.0 (2.3)	7.8 (4.2)
	Declarative Knowledge Score	6.6 (1.3)	7.8 (5.4)	6.6 (2.8)	7.3 (3.8)
	Inference Score	6.4 (3.2)	6.4 (3.0)	6.8 (2.3)	4.7 (3.0)

Table 3

Correlations between pre- and posttests.

		Pretest		Posttest		
		Mental Model	Declarative Knowledge	Mental Model	Declarative Knowledge	Inferential Knowledge
Pretest						
	Mental Model Score	1				
	Declarative Knowledge Score	.34*	1			
Posttest						
	Mental Model Score	.74**	.37*	1		
	Declarative Knowledge Score	.48**	.35*	.51**	1	
	Inference Score	.38*	.29	.42*	.5**	1

*$p < .05$ **$p < .01$

A MANCOVA was conducted to analyze posttest performance; kurtosis and skewness for all variables was within the acceptable range (±2). Explanation type and representation type were independent variables; posttest scores on the mental model assessment, declarative knowledge assessment, and inference items were used as dependent variables. Pretest mental model scores served as the covariate.

Results

Multivariate results. Multivariate results showed a significant effect of the covariate: pretest mental model scores ($F_{(3,28)} = 12.3$, $p < .01$, $\eta_p^2 = .58$). A trend was seen for the main effect of explanation type ($F_{(3,28)} = 2.6$, $p = .07$, $\eta_p^2 = .22$). There was no significant main effect of representation type ($F < 1$). The two-way interaction between explanation type and representation type was not significant ($F_{(3,28)} = 1.1$, $p = .35$, $\eta_p^2 = .11$).

Univariate results. Univariate results were examined in mental model posttest scores, declarative knowledge posttest scores and inference posttest scores.

Mental model posttest scores. Univariate results showed a significant effect of the covariate: premental model scores ($F_{(1, 30)} = 33.2$, $p < .01$, $\eta_p^2 = .53$). There was not a significant main effect of explanation type ($F < 1$) nor a significant main effect of representation type ($F_{(1, 30)} = 2.5$, $p = .12$, $\eta_p^2 = .08$). The two-way interaction between explanation type and representation type was not significant ($F < 1$).

Declarative knowledge posttest scores. Results showed a significant effect of the covariate: pretest mental model scores ($F_{(1, 30)} = 16.6$, $p < .01$, $\eta_p^2 = .36$). As seen in Figure 2, there was a significant main effect of explanation type ($F_{(1, 30)} = 6.2$, p = .02, $\eta_p^2 = .17$). Participants who explained to another scored higher on declarative knowledge items than students who self-explained (see Table 2). There was not a significant main effect of representation type ($F < 1$). Two-way interaction between explanation type and representation type was not significant ($F_{(1, 30)} = 2.0$, $p = .16$, $\eta_p^2 = .06$).

Inference posttest scores. Results showed a significant effect of the covariate: pretest mental model scores ($F_{(1, 30)} = 5.6$, $p = .03$, $\eta_p^2 = .16$). There was not a significant main effect of explanation type ($F < 1$) nor a significant main effect of representation type ($F < 1$). A trend was observed for the two-way interaction between explanation type and representations type ($F_{(1, 30)} = 2.90$, $p =$

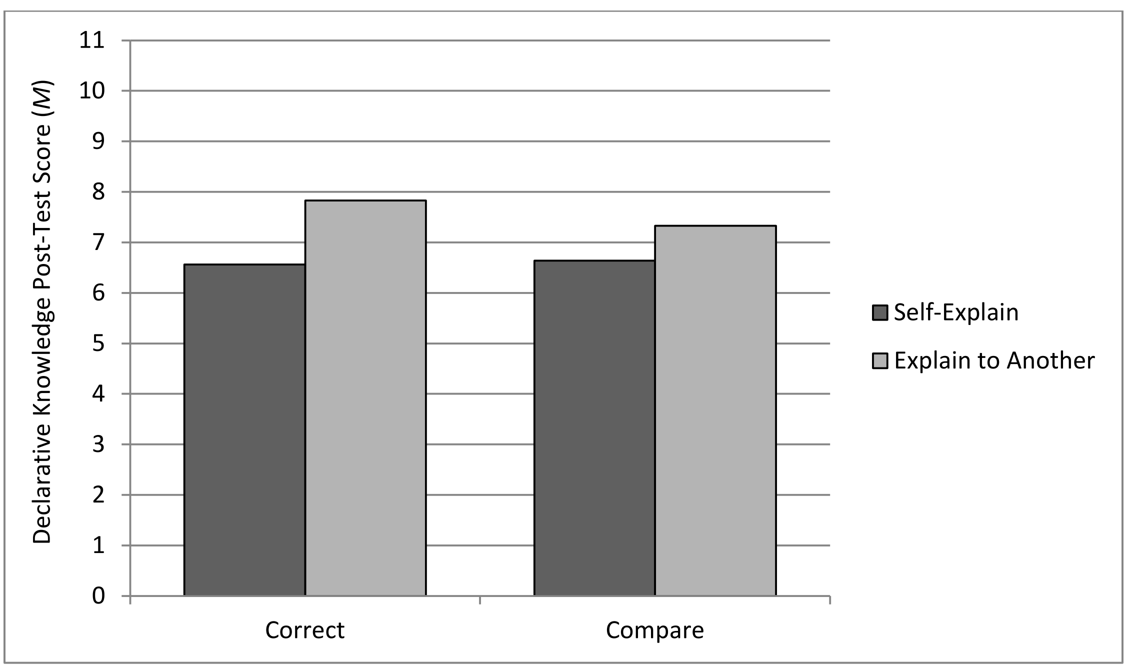

Figure 2. Mean declarative knowledge scores at post-test, by experimental condition.

.10, , $\eta_p^2 = .09$). Learners who self-explained scored higher when comparing the correct and incorrect models than when explaining the correct model alone. In contrast, learners who explained to another with the correct model only scored higher than those who used both the correct and incorrect models (see Figure 3).

Discussion

The first research question in this study asked if self-explanation would be more effective than explaining to a nonpresent peer when visual mental models (or representations) are used during explanation. The answer may depend, partially, on what type of knowledge is being targeted. Results from this research show that students formed more declarative knowledge when explaining to another, compared to explaining to oneself. Declarative knowledge questions

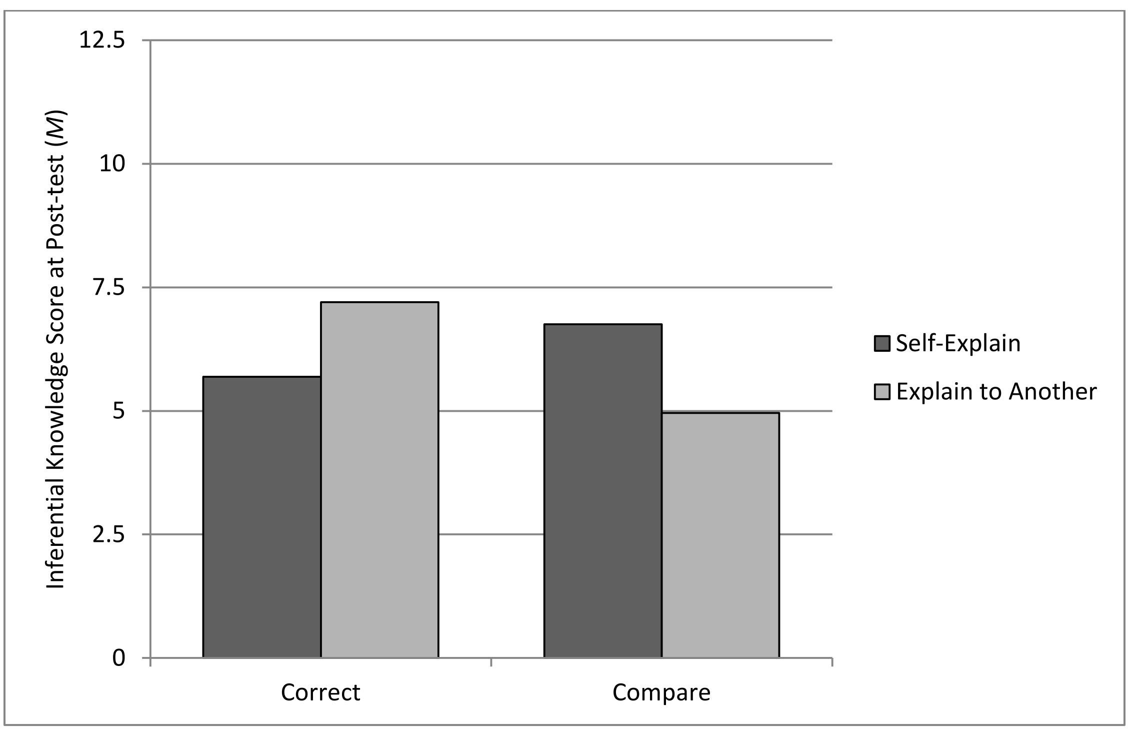

Figure 3. Mean scores on inferential knowledge measure at post-test, by experimental condition.

asked the participant to define the human heart and circulatory system terms or vocabulary. Thus, using visual representations to create an instructional explanation for another student may emphasize encoding of factual knowledge.

This possibility is consistent with prior research (Roscoe & Chi, 2008), which has found that students who create video explanations often fail to engage in knowledge building as opposed to more passive transmission of factual content. However, Roscoe and Chi (2008) found that students engaged in self-explanation were significantly more likely to engage in this type of deeper processing, resulting in better understanding when students self-explained as opposed to creating video explanations. This research found no significant effects of explanation type on mental model scores or inferential knowledge scores. This research suggests that a visual representation may make different forms of explanation more comparable when deeper levels of knowledge are considered. However, more research is needed to determine if the presence of a visual representation is responsible for the equivalent performance on tests of deeper understanding for participants who engaged in different types of explanation during this research.

The second research question addressed by this study was whether explaining with correct and incorrect mental models would be more effective than explaining with a correct mental model alone when recording a video explanation for a nonpresent peer. Results did not demonstrate significant interactions between representation type and explanation type on mental model or declarative knowledge scores, but a nonsignificant trend was observed for inferential knowledge scores. Patterns of results showed that students who self-explained scored higher on the inference items when explaining correct and incorrect mental models as opposed to explaining a correct model alone. In contrast, participants who explained to another scored higher on inference items when explaining the correct model alone compared to explaining the correct and incorrect models. These results suggest that different forms of representations may be optimal for different types of explanations. However, it should be noted that performance overall on the inference items was very poor. Participants who explained the correct model to another were the best performing condition on the inference test, but their mean score was only 28% of the total possible. Thus, more work is needed to better understand when the type of explanation being produced may influence the optimal representation for learning.

The potential benefit of comparing correct and incorrect models during self-explanation in this research is somewhat inconsistent with previous research by Groβe and Renkl (2007). Groβe and Renkl (2007) found that self-explaining both correctly and incorrectly worked-out problems was helpful for high-prior knowledge learners, but not low-prior knowledge (Große & Renkl, 2007). This discrepancy may be related to the different domains in the studies (mathematics vs. biology), or may be related to the nature of the materials being used. It is possible that lower knowledge learners find it easier to compare correct and incorrect biology diagrams compared to correct and incorrect mathematical solutions. More research is needed to better understand these possibilities.

Limitations and Future Directions

The current study was limited to a single study session on a single topic, with no follow-up sessions. Thus, it may not accurately represent authentic situations when learners may revisit materials several times.

Excluding participants with higher prior knowledge resulted in a small number of participants in each experimental condition for analysis. Thus, power to detect potential difference may have been compromised. Future research should attempt to screen for prior knowledge before participation in order to obtain larger sample sizes.

The pattern of results observed in this study suggests that it would be useful to analyze the nature of the explanations produced by students in each condition. However, due to equipment error, screen capture videos included audio for only 5 of the 35 participants (2 in the self-explain and correct model condition, 0 in the explain to another and correct model only, 2 in the self-explain and the correct and incorrect models condition, and 1 in the explain to another and correct and incorrect models condition). Future research should consider implementing protocol analysis in order to understand the potential impact of explanation type and representation type during learning.

Conclusion

Overall, this study suggests some interest possible differences in the knowledge that is formed by different types of explanation as well as some in the types of materials that support understanding when different explanations are created. Low prior knowledge learners who explain to another using visual representations may particularly gain declarative knowledge, compared to students who explain visuals to themselves. When considering deeper understanding, low-knowledge learners who explain to themselves may benefit from comparing correct and incorrect diagrams but low-knowledge learners who explain to another may benefit from working with correct diagrams more than correct and incorrect diagrams.

APPENDIX

NECESSARY FEATURES FOR EACH TYPE OF MENTAL MODEL

1 – Single Loop - Basic

- Blood circulates
- Heart as a pump
- Vessels (arteries/veins) transport
- Purpose of oxygen/nutrient transport

2 – Single Loop with Lungs

- Blood circulates
- Heart as a pump
- Vessels (arteries/veins) transport
- Circulation to the lungs
- Purpose of oxygen/nutrient transport

3 – Double Loop 1

- Blood circulates
- Heart as a pump
- Vessels (arteries/veins) transport
- Purpose of oxygen/nutrient transport
- Loop: heart – body – heart – lungs – heart
- Structural details: vessels, flow through values

4 – Double Loop 2 (Correct Model)

- Blood circulates
- Heart as a pump
- Vessels (arteries/veins) transport
- Purpose of oxygen/nutrient transport
- Loop: heart – body – heart – lungs – heart
- Structural details: vessels, flow through values
- Electrical system, transport functions of the blood, and details of blood cell

REFERENCES

Ainsworth, S., & Loizou, A. T. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27*(4), 669-681. doi: 10.1207/s15516709cog2704_5

Al-Harthi, A. S. (2010). Learner self-regulation in distance education: A cross-cultural study. *American Journal of Distance Education, 24*(3), 135-150. doi: 10.1080/08923647.2010.498232

Ariel, R. (2013). Learning what to learn: The effects of task experience on strategy shifts in the allocation of study time. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39*(6), 1697-1711. doi: 10.1037/a0033091

Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology, 96*(3), 523-535. doi: 10.1037/0022-0663.96.3.523

Azevedo, R., Cromley, J. G., & Seibert, D. (2004). Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia? *Contemporary Educational Psychology, 29*(3), 344-370. doi: http://dx.doi.org/10.1016/j.cedpsych.2003.09.002

Azevedo, R., Guthrie, J. T., & Seibert, D. (2004). The role of self-regulated learning in fostering students' conceptual understanding of complex systems with hypermedia. *Journal of Educational Computing Research, 30*(1/2), 87-111.

Azevedo, R., Moos, D., Greene, J., Winters, F., & Cromley, J. (2008). Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia? *Educational Technology Research & Development, 56*(1), 45-72. doi: 10.1007/s11423-007-9067-0

Braasch, J. L. G., Goldman, S. R., & Wiley, J. (2013). The influences of text and reader characteristics on learning from refutations in science texts. *Journal of Educational Psychology, 105*(3), 561-578. doi: 10.1037/a0032627

Bryant, D. J., & Tversky, B. (1999). Mental representations of perspective and spatial relations from diagrams and models. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*(1), 137-156. doi: 10.1037/0278-7393.25.1.137

Butcher, K. R. (2006). Learning from text with diagrams: Promoting mental model development and inference generation. *Journal of Educational Psychology, 98*(1), 182-197. doi: 10.1037/0022-0663.98.1.182

Chi, M. T. H., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13*(2), 145-182. doi: 10.1207/s15516709cog1302_1

Chi, M. T. H., De Leeuw, N., Chiu, M.-H., & Lavancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science, 18*(3), 439-477. doi: 10.1207/s15516709cog1803_3

Chi, M. T. H., Siler, S. A., Jeong, H., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science, 25*(4), 471-533. doi: http://dx.doi.org/10.1016/S0364-0213(01)00044-1

Clark, R. E. (1983). Reconsidering research on learning from media. *Review of Educational Research, 53*(4), 445-459. doi: 10.2307/1170217

Crowley, K., & Siegler, R. S. (1999). Explanation and generalization in young children's strategy learning. *Child Development, 70*(2), 304.

Eysink, T. H. S., & de Jong, T. (2012). Does instructional approach matter? How elaboration plays a crucial role in multimedia learning. *The Journal of the Learning Sciences, 21*(4), 583-625. doi: 10.2307/42000223

Eysink, T. H. S., de Jong, T., Berthold, K., Kolloffel, B., Opfermann, M., & Wouters, P. (2009). Learner performance in multimedia learning arrangements: An analysis across instructional approaches. *American Educational Research Journal, 46*(4), 1107-1149. doi: 10.2307/40284748

Gadgil, S., Nokes-Malach, T. J., & Chi, M. T. H. (2012). Effectiveness of holistic mental model confrontation in driving conceptual change. *Learning and Instruction, 22*(1), 47-61. doi: http://dx.doi.org/10.1016/j.learninstruc.2011.06.002

Graham, L., & Metaxas, P. T. (2003). "OF COURSE IT'S TRUE; I SAW IT ON THE INTERNET!" Critical thinking in the internet era. *Communications of the ACM, 46*(5), 70-75.

Große, C. S., & Renkl, A. (2007). Finding and fixing errors in worked examples: Can this foster learning outcomes? *Learning and Instruction, 17*(6), 612-634. doi: http://dx.doi.org/10.1016/j.learninstruc.2007.09.008

Hoogerheide, V., Loyens, S. M. M., & van Gog, T. (2014). Effects of creating video-based modeling examples on learning and transfer. *Learning and Instruction, 33*(0), 108-119. doi: http://dx.doi.org/10.1016/j.learninstruc.2014.04.005

Kozma, R. B. (1991). Learning with media. *Review of Educational Research, 61*(2), 179-211. doi: 10.2307/1170534

Kozma, R. B. (1994). Will media influence learning? Reframing the debate. *Educational Technology Research and Development, 42*(2), 7-19. doi: 10.2307/30218683

Moos, D. C., & Azevedo, R. (2008). Self-regulated learning with hypermedia: The role of prior domain knowledge. *Contemporary Educational Psychology, 33*(2), 270-298. doi: http://dx.doi.org/10.1016/j.cedpsych.2007.03.001

Rittle-Johnson, B., & Star, J. R. (2007). Does comparing solution methods facilitate conceptual and procedural knowledge? An experimental study on learning to solve equations. *Journal of Educational Psychology, 99*(3), 561-574. doi: 10.1037/0022-0663.99.3.561

Rook, L. (2013). Mental models: A robust definition. *Learning Organization, 20*(1), 38-47.

Roscoe, R. D., & Chi, M. T. H. (2008). Tutor learning: The role of explaining and responding to questions. *Instructional Science, 36*(4), 321-350. doi: 10.1007/s11251-007-9034-5

Shier, D., Butler, J., & Lewis, R. (2006). *Hole's essentials of human anatomy & physiology* (10th ed.). Boston, MA: McGraw-Hill Higher Education.

Siegler, R. S. (2002). *Microgenetic studies of self-explanation microdevelopment: Transition processes in development and learning*. Cambridge,U.K. ; New York: Cambridge University Press.

Sitzmann, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin, 137*(3), 421-442. doi: 10.1037/a0022777 10.1037/a0022777.supp (Supplemental)

Smith, J. P., III, diSessa, A. A., & Roschelle, J. (1993). Misconceptions reconceived: A constructivist analysis of knowledge in transition. *The Journal of the Learning Sciences, 3*(2), 115-163. doi: 10.2307/1466679

Tenorio, E. H. (2003). New Technologies and education: Challenging disappointment. *Educational Media International, 40*(3/4), 209-218. doi: 10.1080/0952398032000113121

VanLehn, K., Jones, R. M., & Chi, M. T. H. (1992). A model of the self-explanation effect. *The Journal of the Learning Sciences, 2*(1), 1-59. doi: 10.2307/1466684

Vosniadou, S. (2008). *International handbook of research on conceptual change*. New York: Routledge.

Wilke, R. A., & Losh, S. C. (2012). Exploring mental models of learning and instruction in teacher education. *Action in Teacher Education, 34*(3), 221-238.

Winne, P. H. (1995). Inherent details in self-regulated learning. *Educational Psychologist, 30*(4), 173.